Law J, Rush R, King T, Westrupp E, Reilly S.

Early Home Activities and Oral Language Skills in Middle Childhood: A Quantile Analysis.

Child Development 2017

DOI: https://doi.org/10.1111/cdev.12727

Title:

Early home activities and oral language skills in middle childhood: A quantile analysis

Authors:

James Law, PhD[1]

Robert Rush, MSc[2]

Tom King, MSc[1]

Elizabeth Westrupp, PhD[3]

Sheena Reilly, PhD[4]

Contact: James Law, Professor of Speech and Language Science, School of Education, Language and Communication Sciences, Newcastle University, Newcastle-upon-Tyne, Tyne and Wear NE1 7RU UK. E: james.law@ncl.ac.uk

Key words:

Birth Cohort, Millennium Cohort Study, Language development, Ordinal least squares regression, quantile regression, proportionate universalism

ACKNOWLEDGEMENTS

We would like to acknowledge the contribution of the parents and children to the Millennium Cohort Study (doi:10.5255/UKDA-SN-6411-2). The work was carried out as part

[1] School of Education, Language and Communication Sciences, Newcastle University, UK
[2] School of Health Sciences, Queen Margaret University, Edinburgh, UK
[3] Judith Lumley Centre, Latrobe University, Victoria, Australia
[4] Menzies Health Institute Queensland, Griffith University, Queensland, Australia

of the work of the Centre for Research Excellence in Child Language funded through the National Health and Medical Research Council in Australia (APP1023493).

ABSTRACT

Oral language development is a key outcome of elementary school and it is important to identify factors that predict it most effectively. Commonly researchers use OLS regression with conclusion restricted to average performance conditional on relevant covariates. Quantile regression offers a more sophisticated alternative. Using data on 17687 children from UK's Millennium Cohort Study we compared OLS and quantile models with language development (verbal similarities) at 11 years as the outcome. Gender had more of an effect at the top of the distribution while poverty, early language and reading to the child had a greater effect at the bottom. The picture for TV watching was more mixed. The results are discussed in terms of the provision of universal and targeted interventions

Background

Predicting patterns of child development has proved difficult and few areas are more challenging than oral language skills. Such skills are important in their own right but they have also been shown to predict difficulties throughout childhood and into adulthood (Law, Rush, Parsons & Schoon, 2009; Alexander, 2009). A number of studies have identified both positive and negative factors that predict language development. Alongside temporally distal factors such as early poverty (National Institute of Child Health and Human Development Early Child Care Research Network*,* 2005), child gender (Law, Rush, Parsons & Schoon, 2012), birth weight (Barre, Morgan, Doyle & Anderson, 2011), parity (Prime, Pauker, Plamondon, Perlman, & Jenkins, 2014), and whether the child had attended a special care baby unit (Wolke & Meyer, 1999), a series of more common proximal social predictors of later language skills have been identified. These include parental reading to the child (Mol & Bus, 2011), providing learning opportunities such as outings to the park (Becker 2014), and television watching (Close, 2004). These findings tend to be stronger in studies of children with clinical levels of language impairment (Johnson, Beitchman & Brownlie, 2010; Law, Tomblin, & Zhang, 2008) than they are in representative cohort studies (Law, Rush, Anandan, Cox & Wood, 2012; Zambrana, Ystrom, & Pons, 2012). These relationships start early and often persist, but there is some suggestion that the capacity to make predictions may be sensitive to the distribution of the outcome. For example, the differences between the top and the bottom of the distribution remain the same over time (Bradbury, Corak, Waldfogel & Washbrook, 2015) but reduce as a proportion of the age at which those skills are measured (Law, King & Rush, 2014). In such cases traditional Ordinary Least Squares (OLS) regression models which are often the default approach may increase the risk of encountering the 'mean focus fallacy' (Hohl, 2009), namely that predictors operate consistently across the distribution of the dependent variable.

The standard linear regression model makes the assumption that the conditional distributions over the predicted means of the dependent variable for given values of the explanatory variable all have the same variance (homoscedasticity). The "homoscedasticity assumption" does not hold when the amount of variability over the expected value of the dependent variable varies with the independent variable(s). The OLS estimate of the regression coefficient will still be unbiased and the standard errors can be easily corrected as to allow for valid statistical inference, but the homoscedasticity assumption restricts the empirical exploration of the relations between the explanatory and response variable. However, systematic differences in the variability and shape of the conditional distributions over the predicted means at different values of the explanatory variable provide information about potentially important aspects of the relation In this way, standard linear regression may constrain the social scientific understanding of the phenomenon in question.

Long recognized in econometric modeling of income distribution, quantile regression has the potential to further our understanding of attributes of child development processes along the full spectrum of child functioning. Specifically they allow researchers to separate out those predictive factors which are sensitive to social disadvantage and those which are not. In the recent tutorial on the subject in Child Development, Petscher and Logan suggest that topics related to child language and other aspects of development were particularly likely to benefit from quantile approaches (Petscher & Logan, 2014). A quantile approach adds refinement by looking at the capacity of the independent variables to predict levels of the outcome, which may reveal effects very different from the average for some parts of the distribution. This allows an investigation of the independent predictor effect across different specified quantiles, from low through to high scoring, on the outcome. Different score locations on the outcome can be thought of as percentiles or quantiles, (e.g. the median is the 50th percentile or 0.5 quantile, the 0.25 quantile is also known as the 25th centile). The interpretation of the associated variable regression coefficient for a particular quantile is similar to that of linear regression, with the regression coefficient representing the increase in the specified outcome, quantile, produced by a one unit increase in the independent variable associated with that coefficient. Comparison of the effects of the independent variables can be made between each of the quantiles. Of course, it may be that the variation is in and of itself interesting but it is also possible that specific quantiles are of interest for exogenous reasons. For example, there has been considerable recent interest about the best characterization of a specific language impairment (Reilly, Tomblin, Law et al., 2014) and the suggestion made that the tenth centile on a norm referenced language measure should be the designated threshold. This cut-point was chosen for a variety of reasons, mostly concerned with convention and a pragmatic interpretation of prevalence data, but, if it could be demonstrated that the factors predicting language development changed in their impact at that point, this would add weight to the clinical validity of this point in the distribution.

Quantile models have also been used in a variety of health contexts, including child malnutrition, growth and obesity, cancer and hypertension and in Geraci's work on predictors of birth weight in the UK's Millennium Cohort Study (MCS) (Geraci 2012). In a study focusing on 212 children at risk of language impairment, Petrill, Logan, Sawye & Justice (2012) suggested that the relation between storybook reading to emergent child literacy was relatively low across the distribution but much more sensitive at the lower end. In a more recent example, a similar approach was adopted in the MCS cohort to identify differential risk factors on child mental health assessed using the Strengths and Difficulties Questionnaire (Tzavidis, Salvati, Schmid, Eirini, Flouri & Midouhas, 2016).

In developmental terms the question then becomes whether factors predicting outcomes operate in a consistent manner across the distribution of the outcome. A within-child biological model sometimes referred to as the "Barker Hypothesis" would suggest that there are a series of main effect predictors (gender, birth weight, parity etc.) driving outcomes without regard to interaction and do so consistently across the distribution (Barker, 2003; Borrell-Carrio, Suchman, Epstein, 2004). An alternative "social determinants" model sometime characterized as the diathesis-stress model (Zuckerman 1999) or the more specific developmental psychopathology model of Cichetti and colleagues (Cicchetti & Cohen, 1995) would hypothesise interactions across the distribution. A third "proportionate model" would suggest that over time the cumulative effects of early parental behaviours start to load on specific factors, severely skewing the relation between predictor and outcome. The first two options can readily be accounted for in Ordinary Least Squares (OLS) models, the third is likely to be better captured in a quantile regression model.

The relation between findings and policy may be likely to require a more nuanced interpretation (Shonkoff, 2004), in part because they often assume that the association between predictors and outcomes is linear whereas this may not be the case. These, in turn, allow us to operationalize an issue which has attracted considerable attention in recent years namely 'Proportionate universalism'. Proportionate universalism refers to the universal provision of services, where the scale and intensity of service delivery is tailored to individual disadvantage and need (Marmot, Friel, Bell et al., 2008; The Marmot Review, 2010; Marmot, 2015; Law et al., 2013). A variety of different intervention approaches have been suggested (targeted, universal, redistributive and proportional universalism) (Benach, Malmusi,Yasui, Martınez, 2011). Yet how proportionate universalism should be put into practice has not been well articulated. Whether predictors, and thus the potential target of interventions, have the same relation across the distribution given a specific outcome becomes critically important for the targeting of those interventions. Quantile models have the potential to inform the development of both practice and policy. For example we could target children with low language and literacy at five years, as would conventionally be the case or we could identify an outcome, such as language development at the end of elementary school and make a judgement as to which children to target earlier in their lives based on those who are low scorers at 11 years. If there is considerable variation across time, as, for example, we know is the case for language development, making predictions based on how children are likely to perform at time 2 might be a better bet than making predictions based on their profile at time 1. Thus in this context "early" intervention does not just mean intervening when the children are young but instead, intervening as soon as the problem emerges. The time 1 score becomes a risk factor, identifying which children's development trajectories to monitor. The same point is made by Marmot who has suggested that income inequalities per se in the child's life may be less important than their influence on psychosocial outcomes (Marmot, 2010) and it is the pattern of those outcomes that needs to be taken into consideration when planning interventions or services. Universal interventions can have counterintuitive effects of widening social disadvantage (White, Adams & Heywood, 2009), not only because higher social groups take up services more readily, but also because their children may benefit more from the intervention. A quantile model would show this as a greater difference at higher attainment levels. An alternative interpretation would be that a universal intervention should be of disproportionate benefit to those most in need.

Of course, it is first necessary to test whether the quantile model offers more than the more traditional OLS regression approach. If it does, there may be interventions which are likely to have specific impacts at specific points in the distribution, effectively providing a way of articulating how proportional universal may be made to work.

This study aims to investigate:

1. To what extent are within-child (gender), family (parity and poverty), home activities (reading to the child and TV watching), and early language performance associated

with child language performance at eleven years, on average (OLS), and at different quantiles of child language (quantile regression).

2. Are quantile regression analyses more informative about association between the independent and dependent variables than those derived from OLS regression?

Given previous findings in typically developing children (e.g., Petrill, Deater-Deckard, Schatschneider, & Davis, 2007; Taylor & Schatschneider, 2010; Turkheimer & Waldron, 2000), we hypothesize that environment-outcome relations will be stronger at lower levels of the distribution. Furthermore we expect that a number of significant relations will be identified in our “within child” model and our “social determinants” model, but we specifically hypothesize that for many children these early disadvantages become sustained or accentuated, rather than fading with time, so that the predictors have a more concentrated effect at the lower end of the distribution of the relation that would otherwise be missed by OLS models but which would be identified in quantile models.

Method

Data source

The data used in this study come from the Millennium Cohort Study (MCS) in the UK (DOI: 10.5255/UKDA-SN-6411-2), comprising prospective longitudinal data on a cohort of children and others in their household. The survey received ethical approval from the South-West, London, Northern and Yorkshire Multi-Center Research Ethics Committees of the NHS. The MCS is a nationally representative cohort of over 18,000 children born in the UK between September 2000 and January 2002. Informed consent was received from mothers and partners for participation in the study for themselves and their children and verified at each later wave of data collection. Children's households were sampled randomly from a register of those receiving child benefit which has estimated coverage of around 97% of children resident in the UK. Families were first surveyed at 9 months, when 18,818 children from 18,552 families were contacted (72% of those approached). Families were contacted again when children were aged 3 years, 5 years, 7 years and 11 years. Parents were given the opportunity to opt out, and consent was sought and obtained at each contact. The sample characteristics for the eleven year data in the MCS have been summarized elsewhere (Platt, 2014).

Participants

Participants in the current study included a total of 5682 children with language assessment data at 11 years, 32.3% of the original sample. Descriptive statistics are provided in Table 1, and show that 28.2% of families were experiencing poverty when children were 11 years. Just 2.4% of children were born small for gestational age, 18.5% were admitted to a special care unit at birth, and 42.9% were from single-child families. Frequency of parent-reported reading and stories with children were high, although parents reported less frequent trips to the library with their child.

TABLE 1 ABOUT HERE

The dependent variable in the present analyses was child language performance on the British Ability Scales (BAS II) standardized (M 100; SD 15) Verbal Similarities subtest (Elliott, Smith & McCulloch 1997) at eleven years of age. This assessment was originally designed to be used with children aged from 5 years to 17 years and 11 months and has internal, split half reliability 0.92 within our age range; test-retest reliability generally of standardization was 0.91. Correlation with the WISC III similarities scale has been evaluated as 0.60, while the BAS verbal ability composite has a correlation of 0.69 with the corresponding WISC composite (Elliott, Smith & McCulloch, 1997). Verbal Similarities assesses children's verbal reasoning and verbal knowledge: The interviewer reads out three words to the child who must then say how the three things are similar or go together. The child is then asked "What could you call these things". Thus in the ages covered at the eleven year sweep of the MCS, the examiner would commonly start with "syrup, toffee, cake" and then be asked for the common features for "water, oil, blood", "jar, bag, box" etc. All of the children in MCS5 (@11 years) start at the 16th item, as this is the starting point for children of their age. There are decision points after items 28 and 33 where the child's performance decides whether the test stops or continues to the next set of questions. One additional correct item at this age roughly corresponds to 3 additional points scored on the standard score scale used in the analysis.

Independent Variables

A number of groups of variables were hypothesized as potentially affecting the quantile distribution of the BAS Verbal Similarities scale at eleven years. These are captured as child and family factors, home activities and early language skills.

Child and family factors Child birth factors included: admission to the special care, neonatal or Intensive care unit after birth; or child born small for gestational age, defined as birth weight less than 2500g with a gestational age of more than 258 days and admission to a special care baby unit. Family poverty was defined via level of equalized household income less than 60 per cent of the median household income, where income was equalized according to the OECD equivalence scale, and coded as above (0) and below the poverty line. Poverty etc. were calculated at the child's birth. Data on gender and the number of siblings in the household (Parity) were also included.

Home activities (child ages 3 and 5 years). Parental involvement was measured by asking parents:

(a) how often the child was read to, @ 3 years (1-2 x a week or less);

(b) how often the child was read to, @ 5 years (1-2 x a week or less);

(b) how often the child was told stories @5 years (1-2 x a week or less),

(c) how often the child visited the library @5 years (1-2 x a week or less);

(d) how often the child was taken to the library @ 3 years, (1x a month or less);

(d) how often the child was taken to the park @ 5 years (1x a month or less);

(e) How long did the child time spend watching TV @ 3 years (3 hours a day or less);

(f) How long did the child time spend watching TV @ 5 years (3 hours a day or less).

Child vocabulary (child age 3 years). The Naming Vocabulary scale of the British Ability Scales II (Elliott, Smith & McCulloch, 1997) is a standardized verbal scale for children aged 2 years 6 months to 7 years 11 months. Naming vocabulary assesses the spoken vocabulary of young children and had internal, split-half reliability of 0.86 within our age range; test-retest reliability was 0.80 for this age. Correlation with the WPPSI-R vocabulary scale has been evaluated as 0.63, while the BAS verbal ability composite had a correlation of 0.68 with the corresponding WPPSI-R composite (Elliott, Smith & McCulloch, 1997). The test items consist of a booklet of colored pictures of objects which the child is shown one at a time and asked to name. The BAS standardization shows that the naming vocabulary subscale is the most predictive of the early years subscales of the schools age subscales, (r = 0.44) albeit in the age range where their standardizations overlap (up to 7;11).

Analytic plan

To examine the univariable and multivariable effects of the independent factors and verbal similarity score at 11 years OLS and quantile regression models were fitted using the R software environment for statistical computing V.2.15.0.30 31. The quantreg package in R was used for the quantile regression and code provided by Geraci (personal communication) was adapted for the analysis (Lumley, 2004, 2011; Koenker, 2011). The quantile regression models were specified to test for effects at the 0.1, 0.3, 0.5, 0.7, and 0.9 quantiles, (10^{th}, 30^{th}, 50^{th}, 70^{th} and 90^{th} centiles). These quantiles were selected following convention (White, Royston & Wood, 2010) and the estimated factor slope coefficients across these selected points of the distribution were reported with their 95% bootstrap confidence interval. Initially the contribution of the independent variables collected in the MCS was assessed by adding blocks to the regression models as follows: Block 1: child and family factors (child age 9 months); Block 2: home activities (child ages 3 and 5 years); and Block 3: child vocabulary (child age 3 years). Only the factors remaining significant from those univariable regressions are presented in the results section below. The multivariable OLS model was produced for those factors which were found to remain statistically significant in the final multivariable quantile regression model.

Quantile plots were used to summarize the intercept and slope coefficients for the multivariable quantile regression models, which also included the estimates for the associated OLS model. Coefficients with confidence intervals that do not cross zero on their respective y-axes were considered to be statistically significant; the OLS confidence interval can also be compared for overlap with the quantile confidence intervals. The intercept portion of the quantile process plot displays the predicted verbal similarities score when a factor is 0 (y-axis) conditional on the quantile of verbal similarities (x-axis).

There is always a risk that multicollinearity may interfere with the interpretation of such models, especially when seemingly related factors are included within models. Accordingly we checked for collinearity between variables and found it to be within acceptable limits.

All statistical analyses were undertaken between 2014 and 2015.

Missing Data

In order to decrease bias and increase analytical power, we used multiple chained equations (using the MICE package in R) to impute missing data at item level, on the basis that the data were Missing at Random (MAR) (Van Buuren & Groothuis-Oudshoorn, 2011). Estimates were combined across the five imputed data sets. Throughout the analyses sampling weights were employed to adjust for unit nonresponse in the MCS by employing the survey packages for R. Complete case analyses were also performed. Findings from complete case and imputed datasets were similar and for this reason analyses using the imputed data set are presented here.

Results

Table 2 presents the estimated regression coefficients from the univariable OLS regression models. The results show that although child vocabulary at 3 years was not associated with frequency of park and library visits at 5 years old, a one-unit increase on child language performance at 11 years was associated with an approximately 0.3 point increase in naming vocabulary at 3 years. For reading at both child ages 3 and 5, the effect was large, being an increase of 5 and 4 points on average respectively, on naming vocabulary at 11 years for those being read to at least once or twice a week. TV viewing at 3 years old had an effect of roughly 2 points, whereas that at 5 years old was slightly lower at 1.3. Boys were significantly better by about 0.7 on average. Parity results indicated a reduction of 1.6 for each additional child in the family. Being in poverty compared to not being in poverty, revealed a difference in Naming Vocabulary of 4.5 points. The effect for having been in an Special Care Baby Unit or being were “small for dates” was a reduction in outcome of 1 and 2.5 points respectively, compared to their counterparts using Multivariable Quantile and Ordinary Least Squares Regressions

TABLE 2 ABOUT HERE

Table 3 gives the regression coefficients for the quantile regressions with multivariable OLS results included for comparison. As expected, the intercept estimates increased from the .10 quantile (score of 32) to the .90 quantile (score of 62). The analyses are conditional on the outcome score, where higher quantiles were associated with higher observed scores, and thus with higher intercepts compared to intercepts in the lower quantiles.

TABLE 3 ABOUT HERE

Child and Family Predictors of Language Performance

Figure 1a illustrates the consistently negative effect of poverty across the distribution of child language performance. The effect of poverty was similar for quantiles 0.3 to 0.9 and for the OLS average effect, with a difference of approximately 2 points lower for those in poverty compared to those not in poverty. In contrast, the effect of poverty for children scoring low on child language performance was greater, with the difference being more than double that at the other locations on the distribution. The effects for birth factors (admission to special care unit and small for gestational age) did not contribute to the models, and were not included in the final multivariable model. The results for parity (Figure1b) indicate a negative effect for increasing number of siblings in the household associated with child language performance. The quantile regression results showed that this effect was greatest at the lowest and highest quantiles. Gender estimates for female children (Figure 1c) were somewhat similar for the OLS and quantile regression models from the 10^{th} to 70^{th} percentile on child language performance at 11 years, with girls performing less well on this outcome, however, this was much more marked at the high scoring end of the distribution (90^{th} percentile).

The effect of child vocabulary at 3 years was broadly consistent across the OLS estimate and the distribution of child language performance at 11 years, where a unit increase on vocabulary was associated with increasing the score on language performance at 11 years by approximately 0.2.

FIGURES 1a to 1f ABOUT HERE

Home Activity Predictors of Language Performance

The conditional quantile profiles are reported in Figures 1a through 1f, including the OLS estimates for comparison. Two of the five home activity predictors remained in the final model. Parents' reading at least once or twice a week to children at 3 years was associated with improved child language performance of almost 2 points on average (OLS model). The magnitude of the effect varied considerably across the quantiles of child language scores at 11 years, with the strongest effect (4.5 points) evident for children scoring in the lowest quantile for language performance at 11 years, and a null effect evident for children in the 0.7 (but not the 0.9) quantile. Parent report of child TV viewing of less than 3 hours per day when children were 5 years had a positive effect on child language performance at 11 years on average (OLS model), but once again this effect varied considerably across the different quantile of the outcome. A gradient in the effect of lower hours of TV viewing was evident across the quantiles, where the largest effect was apparent for children performing most poorly on language performance at 11 years, and the smallest effect was apparent for children performing in the highest quantile for language performance at 11 years.

Discussion

The current study investigated child, family, and home predictors in the very early years of child language performance at 11 years and compared the utility in such longitudinal models of using standard (OLS) regression models with a quantile regression modeling approach. The findings suggest that quantile regression can be more informative than OLS models, with evidence showing considerable variation in the magnitude of the effect of common predictors of children's language performance, depending on where in the distribution children fall on language performance.

Two broad patterns were demonstrated in the current findings. The first is a profile where OLS and quantile pattern are equivalent except for children who had scores below the

30th centile on the outcome where the impact of the predictor (i.e., family poverty, early vocabulary, parents' reading patterns) becomes more pronounced. Interestingly, one might anticipate that early language scores would be consistent predictors of later performance (i.e. best captured in the OLS model) and indeed this is the case but again we see that there is a striking difference at the lower end of the distribution where the prediction is especially strong. A similar relation is seen in regard to TV viewing. The predictor has a positive effect at the lower end of the distribution but a smaller effect at the top. Again the suggestion is that the distribution of the outcome is very sensitive to the nature of the predictor.

The second type of pattern is best described as an inverted U-shaped distribution, exemplified by parity and gender. In both cases the similar effect is observed at the top and the bottom of the distribution but not in the middle. In others words having more siblings is more negative for children with low scores and for those with high scores but with a smaller effect elsewhere on the distribution. It is of interest in the translation between univariable and multivariable stage of the analysis that poverty and book reading were comparable in their effect at the lower end of the model but poverty was more marked at the top.

Developmental models

We have proposed three potential developmental models, one biologically "within-child model", a second socially driven "social determinants model" controlling for a variety of factors and a third "proportionate" model" suggesting an accumulation of risk at the bottom of the distribution for some variables. Although the interpretation is clearly nuanced and there are some variables which do not weight at the bottom of the distribution there are clearly others that do. We acknowledge that there are a number of factors that are likely to influence children's early behavior and preferences, and subsequent development and that these represent associations across time rather than causal mechanisms. However, our results suggest that an important prior influence is likely to be the parents' past behavior, e.g., in relation to shared book reading and limit setting around TV watching, given that these factors are known predictors of children's later preferences for these activities, particularly in the early years. It is possible that other individual child factors (working memory, attention, activity levels etc.) influence both children's affinity for particular home activities and their language functioning. However, tailored interventions can be designed to take these types of individual differences into account, and can assist parents to engage children in activities even if both parent and child find them difficult.

Implications for Policy and Practice

Application of quantile regression may help in the development of services by identifying whether the performance on the dependent variables of interest (i.e., child developmental outcomes) are sensitive to specific proximal predictors or modifiable risk factors. Our findings show that poverty and parental reading to the child in the early years had by far the strongest effects for children with low language – i.e., at the bottom of the distribution. This would suggest that there may be little added value of universal reading interventions but that interventions targeting the bottom of the distribution would be especially beneficial. By contrast, the data on TV viewing would suggest that graded messages would be appropriate across the full distribution, perhaps involving a universal program for intervention offering increasing intensity to children at the lower end of the distribution. The focus of the intervention from these data would need careful consideration because these data indicate that TV watching may be a protective factor for children with lower language skills at eleven years but a potential risk for those with higher language skills at the same time point. Potentially quantile regression could, as Petscher and Logan (2014) suggested, be use to examine differential treatment effects in population studies and when "scaling up" interventions (Reeves & Lowe, 2009).

Returning to the issue of whether quantiles can help inform the categorization of groups of children, in this case with language impairment. It was suggested that if the distributions changed dramatically at the tenth centile this would give support to the notion of the “psychological reality” of the threshold – at least in terms of the predictors. By psychological reality we mean that the threshold is driven less by arbitrary psychometric convention and more by whether the children with scores falling above and below that threshold were meaningfully different in their profile and performance. The suggestion in these plots is that the threshold may, in fact, be rather higher between the 10^{th} and the 30^{th} centile. This issue would only be resolved with more fine-grained quantile analysis.

Intervention

As indicated above, all the biological, social and parenting variables examined in the quantile models significantly predicted eleven year outcomes and potentially all may be of relevance to the development of interventions. To this extent universal interventions focusing on early literacy and language are likely to be relevant. But the quantile analysis may help us with a more proportionate approach with enhanced input for some sections of the population. An interesting example from these data is gender. It would appear that, while gender is an important consideration across the distribution, there is a marked difference between the boys and girls; at the top end favoring boys and at the bottom end favoring girls. This suggests that higher performing girls in the early years may be likely to slip behind their male counterparts but the time they are eleven years old. Whether one would target girls in this group for intervention in this way is questionable but it is interesting that it does reflect the findings of the descriptive analyses of the MCS at eleven years and also links to work carried out in other cohorts which have shown that many girls do not perform as a well as boys in oral language skills (Law, Rush, Parsons & Schoon, 2012). Overall, the pattern for poverty is as expected, with greater effects at the lower end of the distribution. The pattern for parity is perhaps less anticipated and is likely to be of interest at a practitioner level. Second and later births appear to have an overall negative effect but this effect is stronger at the top and the bottom of the distribution suggesting that practitioner advice to families may need to be tailored to different size families. The pattern for TV viewing does not differ from the OLS model and thus one would argue that recommendations ought to be the same across the population but the uptick at the lower end and the down tick at the higher end suggests that care needs to be taken in assuming that a "turn off the TV" model is the correct one. By contrast the model for early book reading is clear. It is good for everyone but it plays a disproportionate role for children with scores at the lower end of the language distribution. Either way quantile approaches and especially those applied to whole populations as indicated in the present study show potential for testing assumptions underpinning proportionate universalism.

Prospects for future research

This study raises a number of research questions that could usefully be addressed in further investigations. It would be appropriate to test these findings for language development in other, large scale representative population cohorts but to also consider whether there are other population level concerns related to children, for example behaviour or obesity where the same patterns may apply. Consistency of results would add confidence to some public health messages. Testing mediation within these models would give a greater understanding of the mechanisms but estimating such models may be a challenge in quantile. The logical next step would be, of course, to explicitly test potential mediational relations with interventions using experimental designs to establish whether it would be possible to modify the quantile patterns by provided targeted intervention. Of course, a proxy for such trials would be adopting a propensity score matching approach where intervention effects are modelled given certain assumptions in the birth cohorts themselves (Rubin, Rosenbaum & Rubin 1983). This may be especially helpful in the light of the other covariates assessed in the present analysis (Rubin & Thomas, 2000) although it should be noted that caveats have been expressed about such an approach (Peikes, Moreno & Orzol, 2008).

Study Limitations

These analyses were developed to look at a specific set of questions related to commonly identified predictor variables in the preschool period and look at their impact at the end of primary school. It may be that the results are affected by this distance and it is possible that the effects would be more pronounced if the predictors were recorded closer to the outcome. In other words do the quantile specific effects wash out over time? Inevitably there is always a question as to whether the point at which the data were collected – for example reading to the child at two and three years is the optimum time to collect this information. It might argued that relatively few parents are not reading to their children at these ages and that although the overall numbers in this sample were very high the numbers in subgroups may affect the power to detect differences. So if we looked at reading to the child in the first year of life one might get a clearer picture. Inevitably such analyses are subject to the availability of measures. Similarly there has been some discussion recently about the potential role of measurement error on the one hand and regression to the mean on the other and that these may interfere with the interpretation. Regression to the mean is less important when whole populations are considered but, of course, the quantiles may effectively be emphasizing the outer ranges of the distribution. Measurement error is a potentially profound problem especially at three years of age when one might assume that it would be difficult for people carrying out the survey who might have less experience in assessing children. The fact that the lines (Figure 1d) are so close together for the BAS at three years suggests that there was relatively little noise in the distribution and therefore we can be reasonably confident in our interpretation of the data. At this point it is perhaps instructive to look at the spread for TV watching which is much more pronounced. It is less easy to explain the reporting of parity where again the upper and lower bounds are very distinct for the median QR.

One of the great strengths of this study is that the size of the sample makes it possible to look across the quantiles without running up against issues of statistical power. This makes is much easier to interpret findings from very large population representative samples than it does working with smaller and potentially “clinical” samples such as that identified by Petrill et al. (2012). The downside of such large secondary datasets is that almost by definition one has to exploit the available data. For example, in this study we use the word naming and verbal similarities data over time. These two variables reasonably characterize aspects of language and indeed have much in common. However if we wanted to explore this further, for example by looking at verbal comprehension or pragmatic skills potentially underlying these relations, it would not be possible to do this in this data set. Thus the very strength of such datasets potentially becomes their weakness.

Of course, it again might be argued that the relations in the data could best be explained by using polynomial transformations of the predictors or the outcome variable. There could be a problem in trying to interpret such data and the resultant transformations from an empirical point of view. But the approach of using a quantile model allows relations where there is no significant effect at substantial parts of the distribution, which such transformations do not support. These, and effects which are positive for some and negative for others, which are essential for planning universal interventions which reduce gradients in outcomes, and respectively for targeting interventions at groups who would benefit. Our concern in this paper was to speak to this issue of proportionate universalism and such analysis would not have allowed us to do this in a way that quantile models do.

In quantile analysis, it is possible to define thresholds in any number of ways. For example, it would be technically possible to only have two categories of outcome (for example case/not case). Greater emphasis could be placed on distinctions at the lower end of the distribution effectively blocking all children with typical development into a single category. Some investigators have opted for multiple quantiles and one could reasonably argue that the more points across the distribution the better the representation of differential effects across the distribution. In the end, the interpretation depends on the question being asked. Here we had a clinical interest in the group of children below the tenth centile but sought to compare them with a range of groups across the distribution in order to demonstrate the contrast with OLS analyses.

Conclusion

Our results indicate that there are some predictors in these models which function very differently when quantile and OLS models are compared, whereas for others this is not the case. Where such differences occur there is a strong case for adopting the quantile model and this should be routinely tested in such analyses. Our results suggest that this approach has the potential to inform a proportionate universalistic approach to interventions in whole populations because it highlights the variable strength of association for some groups in the population relative to others.

References

Alexander, RJ (2010). Children, their world, their education: Final report and recommendations of the Cambridge Primary Review. London: Routledge.

Barker, D. J. P. (2003). The developmental origins of adult disease [editorial]. Eur J Epidemiol, 18(8), 733-736.

Barre, N., Morgan, A., Doyle, L.W. & Anderson, P.J. (2011). Language Abilities in Children Who Were Very Preterm and/or Very Low Birth Weight: A Meta-Analysis. The Journal of Pediatrics 158, 766–774. DOI: 10.1016/j.jpeds.2010.10.032.

Becker, B. (2014). How often do you play with your child?: The influence of cultural capital and the frequency of familial activities from ages 3 to 6 years. European Early Childhood Educational Research Journal. *22:1, 4-13.* DOI: 10.1080/1350293X.2013.865355

Benach,J. Malmusi,D. Yasui,Y., Martınez,J.M. (2013). A new typology of policies to tackle health inequalities and scenarios of impact based on Rose's population approach. J Epidemiol Community Health 67:286–291. doi:10.1136/jech-2011-200363. DOI: 10.1136/jech-2011-200363.

Borrell-Carrio F, Suchman AL, Epstein RM. (2004) The biopsychosocial model 25 years later: Principles, practice, and scientific inquiry. *Ann Fam Med.*;2(6):576-582.

Cicchetti, D., & Cohen, D. J. (1995a). Perspectives on developmental psychopathology. In D. Cicchetti & D. J. Cohen (Eds.), Developmental Psychopathology: Theory and Methods (Vol. 1). New York: John Wiley and Sons, Inc.

Close, R. (2004). Television and language Development in the Early Review of the literature. London: National Literacy Trust.

Elliott, C., Smith, P. & McCulloch, K. (1997). British Ability Scales, Second Edn. NFER Nelson, London, UK.

Firpo, S. (2007). Efficient Semiparametric Estimation of Quantile Treatment Effects. Econometrica, 75: 259–276. DOI: 10.1111/j.1468-0262.2007.00738.x.

Geraci, M. (2013). Estimation of regression quantiles in complex surveys with data missing at random: An application to birth determinants. Stat Methods Med Res DOI: 10.1177/0962280213484401.

Hohl, K (2009). Beyond the Average Case: The Mean Focus Fallacy of Standard Linear Regression and the Use of Quantile Regression for the Social Sciences (December 22, 2009). Available at SSRN: http://ssrn.com/abstract=1434418.

Johnson, C.J., Beitchman J. H.& Brownlie, E.B. (2010). Twenty-Year Follow-Up of Children With and Without Speech-Language Impairments: Family, Educational, Occupational, and Quality of Life Outcomes. American Journal of Speech-Language Pathology 9, 51–65.

King, T., Rush, R, Westrupp, E., Reilly, S., McKean, C., Law, J (forthcoming). The impact of increasing maternal education on single word reading in middle childhood: An analysis of the Millennium Cohort Study. Merrill Palmer Quarterly.

Koenker R. (2011). quantreg: quantile regression. R package version 4.65. 2011.

Koenker, R. (2005). Quantile regression. New York, NY: Cambridge University Press.

Koenker, R. & Basset, G. (1978). Regression Quantiles. Econometric, 46: 33-50.

Koenker, R. & Hallock, K.F. (2001). Quantile regression: An introduction. Journal of Economic Perspectives ; 15,4,143-156.

Koenker, R. & Machado,JAF (1999). Goodness of fit and related inference processes for quantile regression. Journal of the American Statistical Association 94 (448), 1296-1310.

Law,J., Rush,R., Anandan, C.,Cox, M. & Wood, R. (2012). Predicting language change between three and five years and its implications for early identification: findings from the Millennium Cohort Study. Pediatrics. 130:1 e132-e137. http://dx.doi.org/10.1542/peds.2011-1673

Law,J., Tomblin, J.B. & Zhang, X. (2008). Characterising the growth trajectories of language impaired children between seven and eleven years. Journal of Speech Language and Hearing Research. 51, 739-750. DOI: 10.1044/1092-4388(2008/052).

Law,J. Rush, R, Parsons, S. & Schoon, I. (2009). Modelling developmental language difficulties from school entry into adulthood: Literacy, mental health and employment outcomes. Journal of Speech, Language and Hearing Research 52, 1401-1416. DOI: 10.1044/1092-4388(2009/08-0142).

Law,J., Rush, R., Parsons, S. & Schoon, I. (2012). The relationship between gender, receptive language and literacy from school entry through to adulthood: Findings from the BCS70 birth cohort. International Journal of Speech Language Pathology DOI: 10.3109/17549507.2012.721897.

Law, J., King, T & Rush, R. (2014). Newcastle University Evidence paper for the Read On, Get On coalition: An analysis of Early Years and Primary School Age Language and Literacy Data from the Millennium Cohort Study. London: Save the Children.

Lumley T. (2004). Analysis of complex survey samples. J Stat Software 9: 1–19.

Lumley T. (2011). Survey: analysis of complex survey samples. R package version 3.24-1.

Marmot, M. (2015). The health gap: The challenge of an unequal world. London: Bloomsbury.

Marmot M, Friel S, Bell R, et al. (2008). Closing the gap in a generation: health equity through action on the social determinants of health. Lancet 372:1661e9.

Marmot, M. (2010). The Marmot Review. Fair Society, Healthy Lives: Strategic Review of Health Inequalities in England Post 2010. London: The Marmot Review.

McMahon, S., Stassi, K. & Dodd, B. (1998). The Relationship between Multiple Birth Children's Early Phonological Skills and Later Literacy. Language, Speech and Hearing Services in Schools, 29(1), 11-23.

Mol, S.E. & Bus, A.G. (2011). To read or not to read: A meta-analysis of print exposure from infancy to early adulthood. Psychological Bulletin, 137:267-296. DOI: 10.1037/a0021890.

National Institute of Child Health and Human Development Early Child Care Research Network (2005). Duration and Developmental Timing of Poverty and Children's Cognitive and Social Development From Birth Through Third Grade. Child Development, 76, 795 – 810.

Parsons, S., Schoon,I. Rush,R. & Law,J. (2009). Long-term Outcomes for Children with Early Language Problems: Beating the Odds. Children and Society DOI:10.1111/j.1099-0860.2009.00274.x

Peikes, D.N., Moreno, L. & Orzol S.M. (2008). Propensity Score Matching:A Note of Caution for Evaluators of Social Programs. The American Statistician 62, (3), 222-231 DOI:10.1198/000313008X332016.

Petrill, S. A., Deater-Deckard, K., Schatschneider, C., & Davis, C. A. (2007). Explaining parental influences on reading-related outcomes: An adoption study. *Infant and Child Development, 16*(2), 171-191.

Petrill,S.A., Logan,J.A.R., Sawyer, B.E. & Justice, L.M. (2012). It Depends: Conditional Correlation Between Frequency of Storybook Reading and Emergent Literacy Skills in Children With Language Impairments. J Learn Disabil. DOI: 10.1177/0022219412470518.

Petscher, Y., & Logan, J. A. R. (2014). Quantile Regression in the Study of Developmental Sciences. Child Development, 85(3), 861-881. DOI: 10.1111/cdev.12190

Platt,L. (ed) (2014) Millenium Cohorty Study: Initial findings from the Age 11 study. London: Institute of Education.

Plewis, I. (2007). Non-Response in a Birth Cohort Study: The Case of the Millennium Cohort Study. International Journal of Social Research Methodology, 10, 5, 325-334 DOI:10.1080/13645570701676955.

Prime, H., Pauker, S., Plamondon, A., Perlman, M. & Jenkins, J. (2014). Sibship size, sibling cognitive sensitivity, and children's receptive vocabulary Pediatrics, 133, 394-401. DOI: 10.1542/peds.2012-2874.

Reeves, E.B. & Lowe, J. (2009). Quantile regression: An educational policy research tool. Southern Rural Sociology 24, 175-199.

Reilly,S. Tomblin, B., Law, J. McKean, C., Mensah, F. Morgan, A., Goldfeld, S., Nicholson, J. & Wake, M. (2014). Specific Language Impairment: a convenient label for whom? International Journal of Language and Communication Disorders. 49, 416-451. DOI: 10.1111/1460-6984.12102.

Royston, P. (2004). Multiple imputation of missing values. The Stata Journal. 4, 227–241.

Rubin, D. B. (1987). Multiple imputation for non-response in surveys. New York: John Wiley & Sons.

Rubin, D. Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70, 41–55.

Rubin D.B. & Thomas, N. (2000). Combining Propensity Score Matching with Additional Adjustments for Prognostic Covariates. Journal of the American Statistical Association 95, (450), 573-585 DOI:10.1080/01621459.2000.10474233.

Schafer, J. L., & Olsen, M. K. (1998). Multiple imputation for multivariate missing-data problems: A data analyst's perspective. Multivariate Behavioral Research, 33(4), 545-571.

Shonkoff, J.P. (2004). Science, Policy, and the young Developing Child: Closing the Gap between what we know and what we do. Chicago, Illinois.

StataCorp. (2013). Stata Statistical Software: Release 13. College Station, TX: StataCorp

Taylor, J., & Schatschneider, C. W. (2010). Genetic influence on literacy constructs in kindergarten and first grade: Evidence from a diverse twin sample. Behavior Genetics, 40, 591-602.

Turkheimer, E. & Waldron, M. C. (2000). Nonshared environment: A theoretical, methodological, and quantitative review. Psychological Bulletin, 126, 78-108.

Tzavid.is,N. Salvati,N. Schmid, T., Eirini Flouri, E. & Midouhas, E. (2016) Longitudinal analysis of the strengths and difficulties questionnaire scores of the Millennium Cohort Study children in England using M-quantile random-effects regression. J. R. Statist. Soc. A DOI: 0964–1998/16/179000.

Van Buuren S and Groothuis-Oudshoorn K. (2011). MICE: multivariate imputation by chained equations in R.. J Stat Software 45: 1–67. http://www.jstatsoft.org/v45/i03/

White, I.R., Royston, P. & Wood, A.M. (2011). Multiple imputation using chained equations: Issues and guidance for practice. Statist. Med. 30 377–399. doi: 10.1002/sim.4067.

White,M., Adams,J. & Heywood, P. (2009). How and why do interventions that increase health overall widen inequalities within populations. In S.J. Babones (ed) Social inequality and public health. Bristol, UK: Policy Press.

Wolke, D. & Meyer, R. (1999). Cognitive status, language attainment, and pre-reading skills of 6-year-old very preterm children and their peers: the Bavarian Longitudinal Study. Developmental Medicine & Child Neurology 41, 94-109.

Zambrana, I.M., Ystrom, E. & Pons, F. (2012). Impact of gender, maternal education, and birth order on the development of language comprehension: a longitudinal study from 18 to 36 months of age. Journal of Developmental & Behavioral Pediatrics, 33(2), 146-155. DOI: 10.1002/sim.40

Zuckerman M. (1999).Vulnerability to psychopathology: A biosocial model. American Psychological Association.

Table 1 Sample characteristics

			Picture Similarities @ 11 years		
			Overall	lowest 10%	highest 10%
Predictor	Categories	% (N)	Mean(SD)	Mean(SD)	Mean(SD)
Child and family factors					
Family poverty (at birth)	Not	71.8 (12663)	61.63(8.78)	39.2 (8.17)	75.32 (3.11)
	Poverty	28.2 (4975)	58.00(9.51)	39.93 (5.71)	74.48 (3.39)
	Missing	0.3 (50)			
Child gender	Male	51.4(9094)	62.1 (8.91)	39.83 (7.57)	75.49 (3.14)
	Female	48.6 (8593)	60.61 (8.82)	39.08 (7.83)	74.94 (3.1)
	Missing	0 (0)			

Child small for gestational age	Not	97.6 (17100)	61.42 (8.9)	39.32 (7.67)	75.27 (3.13)
	Small for gestational age	2.4 (417)	56.83 (7.34)	40.84 (12.68)	75.16 (3.47)
	Missing	1(171)			
Parity	0	42.9(7584)			
	1	36.2(6408)			
	2	14.4(2556)			
	3	4.5(789)			
	4	1.3(230)			
	5	0.4(74)			
	6	0.2(34)			
	7	0.1(9)			
	8	0(2)			
	9	0(2)			
	Missing	0(0)			

Special care unit admission	SCU	18.5 (1553)	60.83 (9.1)	35.69 (9.49)	75.15 (3.04)
	Not	81.5 (6833)	61.44 (8.85)	40 (7.23)	75.29 (3.15)
	Missing	52.6 (9302)			
	coding	% (N)			
Home activities with child					
Parent read to child @ 3 years	Less than once or twice a week	2.8 (293)	57.32 (8.49)	38.45 (6.69)	74.88 (3.55)
	At least once or twice a week	97.2 (10264)	61.37 (8.89)	39.38 (7.69)	75.26 (3.12)
	Missing	40.6 (7130)			
Read to child @ 5 years	Less than once or twice a week	1.7 (176)	58.07 (9.26)	37.65 (6.69)	73.64 (2.28)
	At least once or twice a week	98.3 (10330)	61.36 (8.89)	39.23 (7.69)	75.29 (3.13)

	Missing	40.8 (7182)			
Parent tells stories @5 years	Less than once or twice a week	27.2 (2860)	60.16 (9.61)	37.49 (9.86)	76.38 (2.94)
	At least once or twice a week	72.8 (7641)	61.74 (8.6)	40.49 (5.84)	75.02 (3.12)
	Missing	40.9 (7186)			
Visits to library @ 3 years	Once a month or less	63.8 (4112)	61.28 (9.18)	38.77 (7.76)	75.42 (3.09)
	More than once a month	36.2 (2335)	61.44 (8.34)	40.43 (7.6)	74.9 (3.21)
	Missing	63.9 (11241)			
Visits to library @5 years	Less than once or twice a week	91.1 (13059)	61.39 (8.92)	39.33 (7.71)	75.38 (3.12)
	At least once or twice a week	8.9 (1274)	60.93 (8.71)	39.63 (8.12)	74.43 (3.09)

	Missing	19.1 (3355)			
Visits to park @ 5 years	Once a month or less	39.2 (5621)	61.97 (8.66)	39.99 (8)	75.26 (3.27)
	More than once a month	60.8 (8708)	61 (9)	39.1 (7.63)	75.27 (3.05)
	Missing	19.1 (3359)			
TV use @ 3 years	More than 3 hours	16 (2329)	59.96 (8.83)	39.09 (5.76)	74.55 (3.06)
	Less than 3hours	84 (12254)	61.5 (8.89)	39.4 (8.06)	75.32 (3.13)
	Missing	17.7 (3105)			
TV use @ 5 years	More than 3 hours	14.1 (2017)	60.71 (7.96)	43.1 (5.03)	75.81 (3.28)
	Less than 3hrs	85.9 (12314)	61.42 (9.01)	38.83 (7.88)	75.21 (3.12)
	Missing	19.1(3356)			

Child language assessment		
	Mean(SD)	% (N)
Naming Vocabulary @ 3 years	50.82(10.82)	23.8 (4192)
Picture Similarities @ 11 years	59.24(9.59)	32.3 (5683)

Table 2 Predictors of child language performance at 11 years: Univariable OLS regression analysis

Variable (split)	B (95% CI)
Library @ 5 years (<1 -2 a week)>1-2 a week)	0.50 (0.09, 0.91)
Park @ 5 years (<=once a month >once a month)	0.11 (-0.46, 0.25)
Reading @ 3 years (<1 -2 a week) >1-2 a week)	5.06 (4.04, 6.09)
Reading @ 5 years (<1 -2 a week) >1-2 a week)	4.26 (3.05, 5.48)
Stories @ 5 years ((<1 -2 a week) >1-2 a week)	0.58 (0.16, 0.99)
TV @ 3 years (>3hours <less than 3hrs)	1.81 (1.3, 2.32)
TV @ 5 years (>3hours <less than 3hrs)	1.33 (0.75, 1.91)
Poverty (not in poverty; in poverty)	-4.53 (-5.04, -4.02)
Parity	1.17 (-1.37, -0.96)
Gender (male/female)	0.74 (-1.10, -0.39)
Special Care Unity CU (SCU; no SCU)	1.10 (0.62, 1.57)
BAS Naming Vocabulary - T-scores @ 3 years	0.27 (0.25, 0.29)

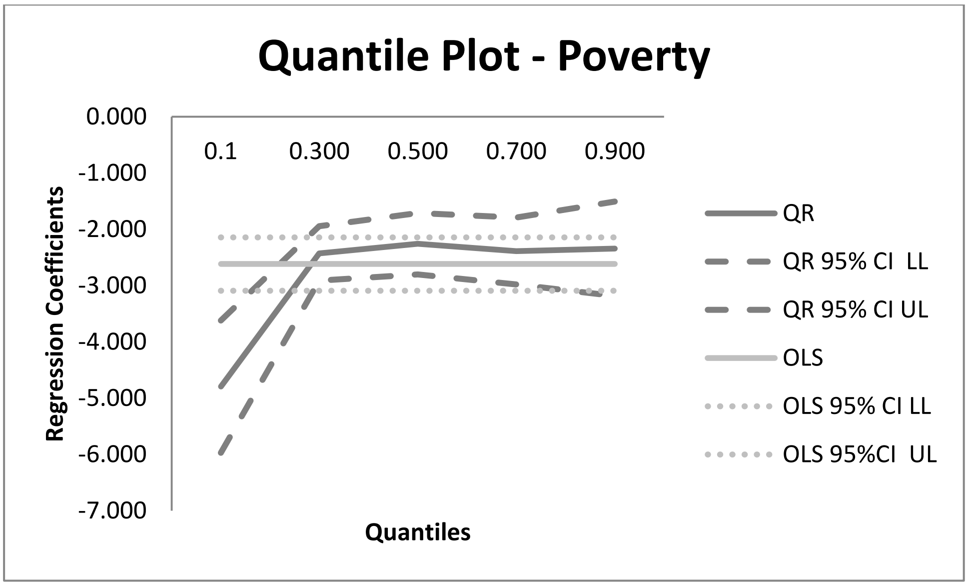
Table 3 Regression coefficients for Multivariable Ordinary Least Square and quantile regressions.

Predictor	**OLS**	**Quantiles**				
		0.1	0.3	0.5	0.7	0.9
	B (95% CI)	B (95% CI)	B (95% CI)	B (95% CI)	B (95% CI)	B (95% CI)
Intercept	47.90 (46.47, 49.32)	32.12 (28.96, 35.27)	45.07 (43.47, 46.66)	49.41 (47.82, 51.00)	54.00 (52.25, 55.74)	62.70 (59.75, 65.66)
Poverty	-2.62 (-3.09, -2.14)	-4.80 (-5.97, -3.62)	-2.43 (-2.91, -1.95)	-2.26 (-2.80, -1.71)	-2.38 (-2.98, -1.79)	-2.34 (-3.18, -1.51)
Parity	-0.42 (-0.59, -0.26)	-0.52 (-0.91, -0.12)	-0.28 (-0.47, -0.09)	-0.30 (-0.48, -0.10)	-0.46 (-0.67, -0.24)	-0.59 (-0.89, -0.29)
Gender (Female)	-1.44 (-1.74, -1.14)	-1.50 (-2.10, -0.89)	-1.14 (-1.47, -0.81)	-1.31 (-1.66, -0.96)	-1.40 (-1.81, -1.00)	-2.33 (-2.92, -1.74)
Vocabulary at 3 years	0.24 (0.22, 0.25)	0.29 (0.26, 0.33)	0.20 (0.18, 0.22)	0.20 (0.18, 0.22)	0.21 (0.19, 0.24)	0.21 (0.18, 0.24)

Reading at three years	1.88 (0.93, 2.82)	4.55 (1.90, 7.20)	1.60 (0.54, 2.66)	1.78 (0.89, 2.66)	1.04 (-0.04, 2.12)	1.45 (-0.11, 3.00)
TV watching at five years	0.80 (0.34, 1.25)	1.28 (0.36, 2.20)	0.96 (0.45, 1.47)	0.79 (0.27, 1.31)	0.79 (0.21, 1.36)	0.54 (-0.31, 1.39)

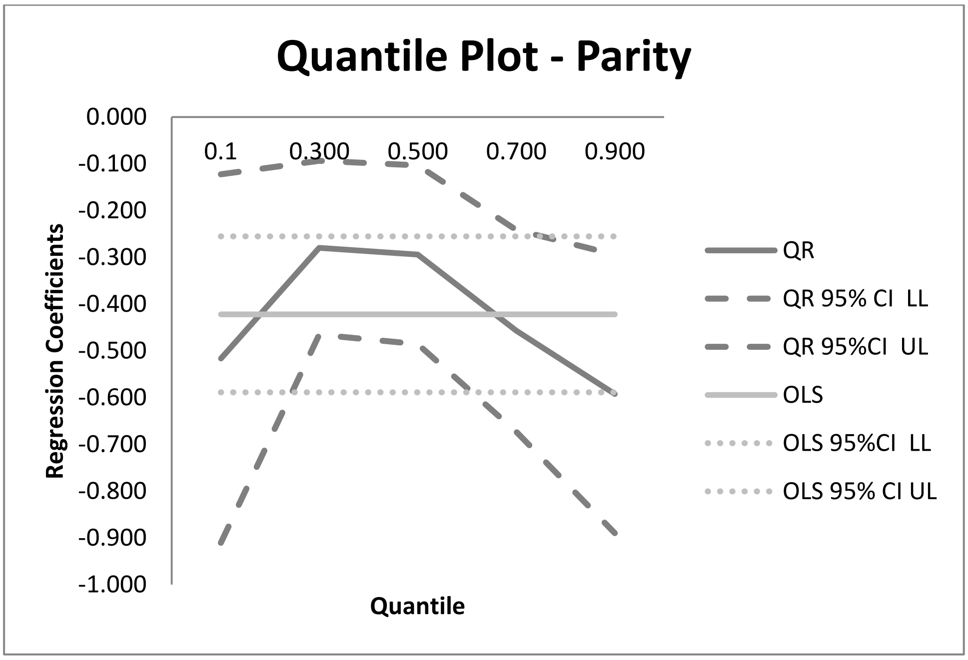
Figures

Figure 1a Quantile plot for Poverty



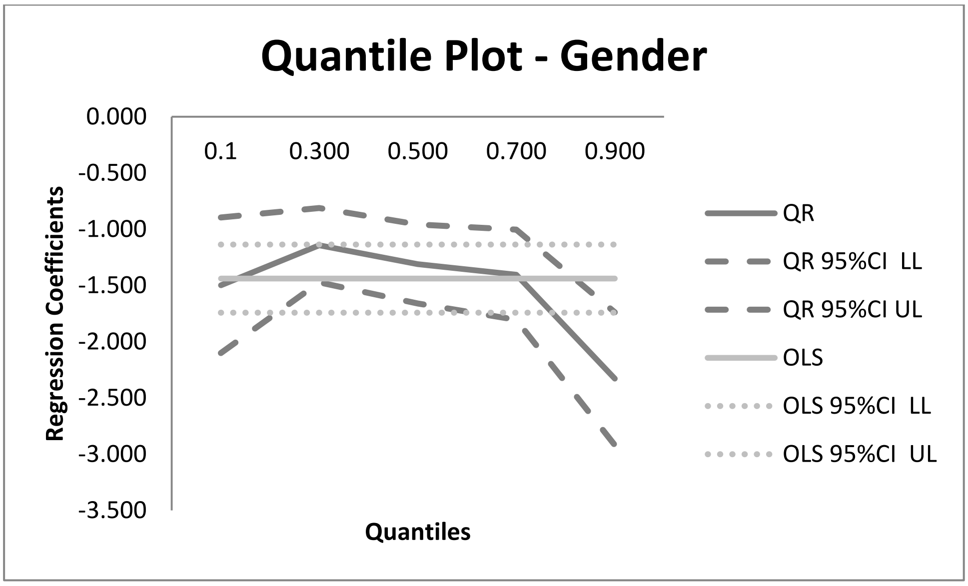
Light gray and dotted lines represent OLS, with 95% CI. Dark gray dashed lines represent quantile regression results, with 95% CI.

Figure 1b Quantile plot for Parity



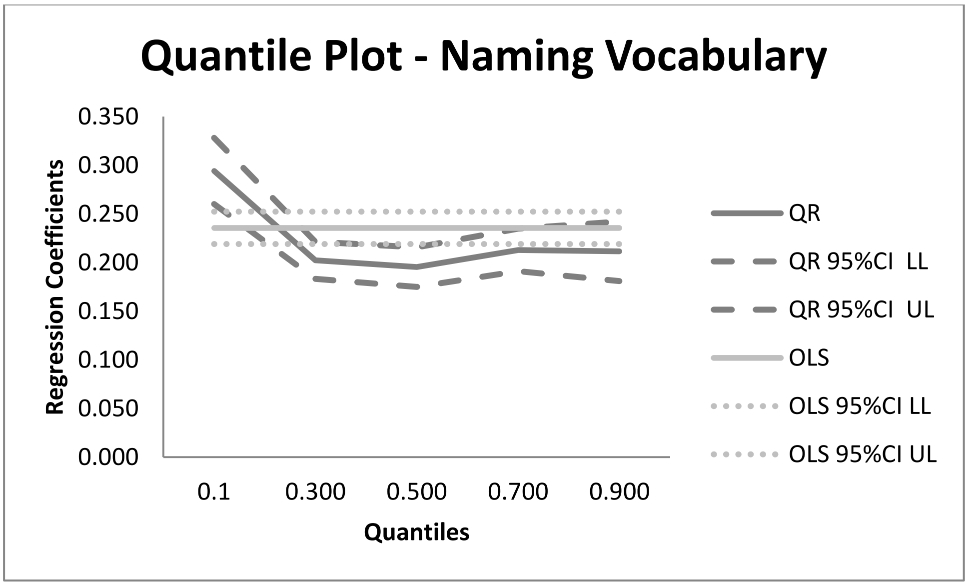
Light gray and dotted lines represent OLS, with 95% CI. Dark gray dashed lines represent quantile regression results, with 95% CI.

Figure 1c Quantile plot for Gender



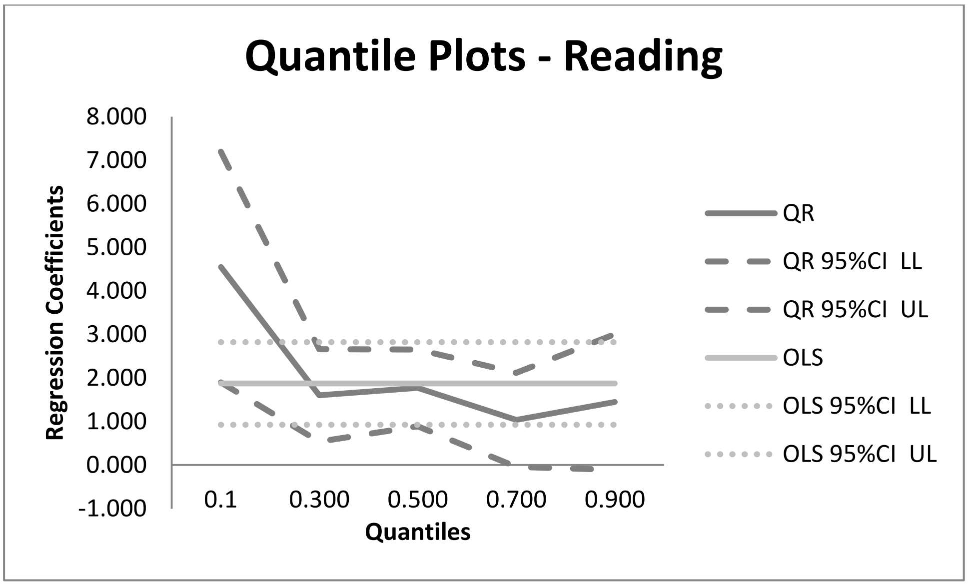
Light gray and dotted lines represent OLS, with 95% CI. Dark gray dashed lines represent quantile regression results, with 95% CI.

Figure 1d Quantile plot for naming vocabulary at three years



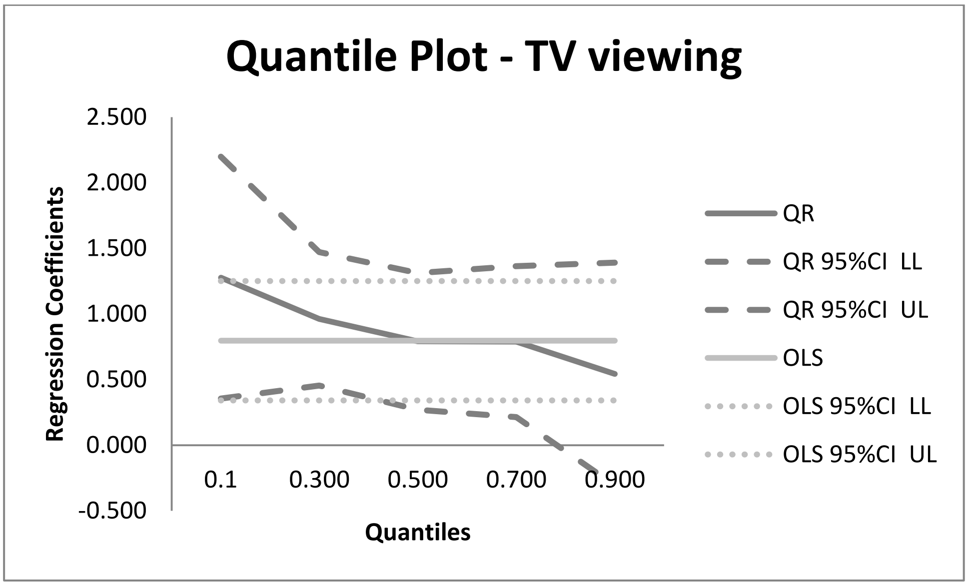
Light gray and dotted lines represent OLS, with 95% CI. Dark gray dashed lines represent quantile regression results, with 95% CI.

Figure 1e Quantile plot for reading at three years



Light gray and dotted lines represent OLS, with 95% CI. Dark gray dashed lines represent quantile regression results, with 95% CI.

Figure 1f Quantile plot for TV viewing at five years



Light gray and dotted lines represent OLS, with 95% CI. Dark gray dashed lines represent quantile regression results, with 95% CI.